Low-dose CT Image Processing and Reconstruction with Deep Learning

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Outline

- Introduction
- Motivation: Using deep learning to improve the image quality of low dose CT
- Low dose CT denoising using deep learning
  - Denoising using cascaded CNN

- Low dose CT Reconstruction using deep learning

- Conclusion and Future Work
  - Deep Learning Can Help Low Dose CT Reconstruction!
  - A Better Framework/Network?
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Image Recon and Analysis

Image Recon:
- PET
- CT
  - Low Dose CT
  - Spectrum CT/Material Decomposition
  - Phase Contrast CT
  - Static CT / Nano CT
- MRI/Optical
- Microscope – EM
- Hybrid: PET/CT, PET/MRI

Image Analysis:
- Image Denoising and Restoration
- Segmentation and Registration
- Novel Image Biomarkers
- Radiomics/Radiogenomics
- Diagnosis/Prognosis

Artificial Intelligence in Medicine

Deep Learning Methodology:
- High Dimensional CNN
- Missing Data Problem
- Learning Annotation
- Transfer Learning
- Novel Network Structures
- Optimization/Compression Networks

Deep Learning Applications:
- Tumor Detection in Digital Pathology
- Emphysema / Pneumothorax Detection
- Lung Cancer Detection
- AD detection
- Diagnosis and Prediction of COPD
- Prediction of the Progression of Diabete
- ........
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First Place!
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Low Dose CT Grand Challenge

- First CT Grand Challenge
- Public Available Data and Parameters
- An Open Test Bed for CT Algorithms

First Place!

Spatially Encoded Non-Local Penalty

Traditional non-local mean
New non-local mean

World Wide Participants
Typical Low-dose CT

ICRP recommended 1-year public dose limit: **1mSv**

<table>
<thead>
<tr>
<th>Method</th>
<th>Assumption</th>
<th>Pros</th>
<th>Cons</th>
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<tr>
<td>Mean Filter</td>
<td>I.i.d. Gaussian noise</td>
<td>Simple</td>
<td>Severe Blurring</td>
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<tr>
<td>Total Variation</td>
<td>Piecewise constant</td>
<td>Edge-preservation</td>
<td>Staircase artifacts</td>
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<tr>
<td>Non-local Mean</td>
<td>Self similarity</td>
<td>Better performance</td>
<td>Edge blurring</td>
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<td>KSVD</td>
<td>Image patches are low-rank</td>
<td>Even better performance</td>
<td>Time-consuming</td>
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**Deep Learning**

- Deep learning can automatically capture important features in the images

- Deep learning is a subset of machine learning that uses many layers (>= 3 except for input and output layers) of nonlinear units for feature extraction

Cascaded Learning

- Use cascaded CNN to compensate for the spiky artifacts in the results
  - After a CNN was trained, it was used to process the training dataset then a new CNN was trained with the processed data

1 CNN

8 cascades of CNNs
Results

180mAs (normal dose)

Noisy 45mAs SSIM = 0.661

CNN 45mAs SSIM = 0.753
Deep Learning Based CT Recon

Image Denoising

Pros:
- Real time
- Greatly improved SNR

Cons:
- Chances for generating false positivity
- “What was lost is lost”

Image Reconstruction

Pros:
- Better image quality
- Lower false positivity rate

Cons:
- Slow
- Image noise changes during iterations

- Iterative CT image reconstruction problem is usually formulated as

\[
x = \arg \min_x \|Ax - p\|_w^2 + \lambda R(x; \theta)
\]

Fidelity term with system matrix \(A\), raw data \(p\) and noise matrix \(w\)

Penalty term with penalty function \(R\), its parameters \(\theta\) and hyperparameter \(\lambda\)
Train Prior Functions with Deep Learning

- Because noises in $\mathbf{x}$ changes during the iterations, it has to be learned in an **unsupervised** way;

- A solution with denoising autoencoders:

$$
\mathbf{x} = \text{arg min} \| A\mathbf{x} - \mathbf{p} \|_w^2 + \lambda \| \mathbf{x} - f(\mathbf{x}) \|_2^2
$$

$f(\mathbf{x})$ is the trained neural networks

**No need for noise simulation**

Results

180mAs (normal dose)

TV 45mAs SSIM = 0.851

Learning 45mAs SSIM = 0.863
Quantitative Results

• SNR – SSIM tradeoff for different hyperparameters
  • Higher SNR – better noise suppressing
  • Higher SSIM – better structural preservation

Best tradeoff point for noise suppressing and structure preservation
Future Works

• “No ground truth” learning
  • Eliminate the need of precise noise modeling

• Reinforcement learning
  • Eliminate the need of hyperparameter tuning for reconstruction

• Diagnosis oriented learning
  • Generate images most suitable for diagnosis
  • Reduce false positive / negative rates
Thanks for your attention!

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